Proceedings – 23rd Annual Conference – IEEE/EMBS Oct.25-28, 2001, Istanbul, TURKEY

EEG SIGNALS CAN BE USED TO DETECT THE VOLUNTARY HAND MOVEMENTS BY USING AN ENHANCED RESOURCE-ALLOCATING NEURAL NETWORK

Abbas Erfanian and Mahdi Gerivany
Biomedical Engineering Group, Department of Electrical Engineering, Iran University of Science and Technology, Narmak, Tehran, 16844, IRAN
E-mail: erfanian@sun.iust.ac.ir

***Abstract*—This article explores the use of single trial EEG signals to predict the voluntary movements of single hand and two hands. During single-hand movements, three kinds of task, *grasping*, *releasing*, and *holding* were considered. The tasks considered during two-hand movements are *left and right grasping*, *left and right releasing*, and *holding*. The subject performs the tasks spontaneously without waiting for and responding to any external cues. In addition, a neural adaptive noise canceller is developed that accomplishes eye blinks suppression. The neural adaptive filter is here implemented by means of a three-layer feed-forward neural network. The feature vectors are formed from the three channels (Fz, C3, and F3). We employ the multilayer perceptron (MLP) with back-propagation learning algorithm and Radial Basis Function (RBF) network with stochastic gradient learning rule for discriminating different patterns of the EEG signals. In the classical approach to RBF and MLP network implementation, the number of hidden units is predetermined. It, usually, results in too many hidden units. To overcome this drawback, we develop an enhanced resource-allocating network (RAN) for discriminating the EEG patterns. These networks start with no hidden units and grow by allocating new hidden units based on the novelty in the EEG signals, which arrive sequentially. The results of this analysis show that the neural networks would be able to detect the movements of a single hand and two hands with an average classification accuracy of 98.82% and 96.40%, respectively. Moreover, the RAN provides a reduction in the training epochs as compared to the MLP and RBF networks. This work represents a promising approach to control prosthesis device.**

Index Terms—EEG, brain, computer, neural network, human-computer interface, adaptive filter, hand movement.

I. INTRODUCTION

It has been known that the intrinsic processes of planning and preparation of a voluntary movement are reflected by the cortical potentials [1], [6]. These suggest the possibility of using the event-related EEG signals to observe the brain processes during attentional demand. In [2], two snapshots of Readiness Potentials recorded from twelve channel surface electrodes were used for recognition of four-direction joystick movements by using neural network. After 1000 training epochs, 23 out of 24 new patterns were correctly recognized.

In [3], the neural network based classification of event-related EEG has been investigated while the task was to push a button with either the left or right index finger. The recorded EEG during 1-s time interval before the physical movement is broken down into overlapped windows. The maximum power value within the alpha band (5-16 Hz) within each window was used as the feature. The features were formed from the multi-channel EEG. The 80% of the experimental trials was used for training and 20% for testing the classifiers. It was reported that the accuracies as high as 85-90% are achieved for two-class classification. In [4], the EEG data from three bipolar channels (C3-C3', Cz-Cz', C4-C4', C3, Cz, and C4) were classified to detect three kinds of movements, left and right index finger, and right foot movement. An accuracy of about 60% was reported. In [5], 56-channel EEG signals have been used to detect three kinds of movements, left and right index finger, and right foot movement. By Laplace filtering the 56-channel EEG, 30-channel EEG data were obtained. For each of the 30 channels, a feedforward neural network was trained with back-propagation learning algorithm. It was reported that a classification accuracy of 92-99% is obtained.

In this work, we used 3-channel EEG data from a single trial to detect the voluntary hand movements using artificial neural network (ANN). A neural network-based adaptive noise canceling was developed for suppression of the eye blink artifact.

II. EXPERIMENTS

The EEG data of a normal subject were recorded at a sampling rate of 256 from positions Fz, C_3, and F3 by scalp electrodes placed according to the International 10-20 system. Another channel was added to record eye blinks by placing an electrode on the forehead above the left brow line. These four channels were referenced to the right earlobe.

During the experiments reported here, two different experimental settings were considered. The first setting consisted of single-hand movements *included grasping, releasing*, and *holding*. The second experimental setting consisted of two-hand movements. The tasks to be performed during two-hand movement included *left and right grasping*, *left and right releasing*, and *holding*. During each trial experiment, one task was voluntarily performed without any external constraint. During holding, the subject did not perform a specific task.

Data were recorded for 5 s during each trial experiment and each trial was repeated 100 times for each task during single-hand movements and 60 times during two-hand movements. During each experiment day, 300 trials were conducted. There were five separate experiment days on the same subject.

0-7803-7211-5/01$10.00©2001 IEEE

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle EEG Signals Can be Used to Detection the Voluntary Hand Movements by Using an Enhanced Resource-Allocating Neural Network	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) Biomedical Engineering Group Department of Electrical Engineering Iran University of Science and Technology Narmak, Tehran Iran	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)

Distribution/Availability Statement
Approved for public release, distribution unlimited

Supplementary Notes
Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Oct 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom., The original document contains color images.

Abstract

Subject Terms

Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU

Number of Pages
4

III. Neural Adaptive Filters

Neural adaptive filters (NAF's), which are based upon the artificial neural network, are used for adaptive processing of a signal [7]. The structure of the neural adaptive filtering applications is much analogous to that of the classical adaptive filtering. Fig. 1 shows a typical application of NAF for noise canceling with the reference signal. In this paper, we apply neural adaptive noise canceling with the reference signal for suppression of the eye blink artifact. The primary signal is the desired signal of interest buried in noise, while the reference input contains noise, which is correlated with the noise component of the primary signal.

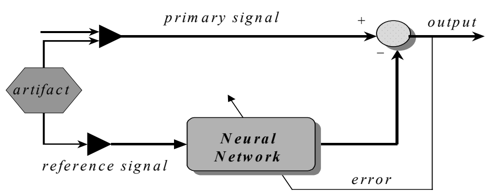

Fig. 1. Neural adaptive filter for noise canceling with reference signal.

IV. Eye Blink Artifact Suppression Using Neural Adaptive Filter

The EEG signals are contaminated by noise from sources such as eye blinks. The traditional method of the eye blink suppression is the removal of the segment of EEG data in which eye blinks occur. Eye blinks are usually detected by means of data recorded from electrodes placed above and below the subject's left eye. An eye blink is said to have occurred if the signal amplitude exceeds a given threshold. All EEG segments in which eye blinks occur are then excluded. This scheme is rigid and does not lend itself to adaptation. Moreover, a great number of data is lost.

To overcome these problems, we employed neural adaptive noise canceller to suppress the eye blink artifact. The NAF was here implemented by means of a multi-layer perceptron (MLP) network with two hidden layers and one Linear output. For the two hidden layers, the activation function is the hyperbolic tangent. The primary signal is the measured EEG data while the reference signal is the data recorded from electrode placed on the forehead above the left brow line. The output of the neural network is an estimate of the noise in the primary signal and the output of the NAF is an estimate of the artifact-free EEG.

For each of the three EEG channels, a NAF was trained and validated. For this purpose, the EEG data along with eye blink data were recorded continuously for 100 s, while the subject did not perform a specific task during recording. The NAF's were trained with the first 18-s segment of data and were evaluated with the subsequent 72-s segment of the data. Fig. 2 shows the eye blink artifact suppression obtained using neural adaptive filter.

V. Neural Network Classifiers

A. Feature Extraction

To classify the EEG patterns, feature vectors must be created. The features were formed from the three channels (Fz, C_3, and F3) during each trial of experiment. The mean absolute value (MAV), variance, the relative power of the beta band to the alpha band, the relative power of the beta band to the total power, the relative power of the alpha band to the total power, and the singular values [8] of the artifact-free EEG constitute the features. Various feature vectors were formed and were fed into the classifiers.

B. Neural Networks

In this work, we employed the multilayer perceptron (MLP) with back-propagation learning algorithm [9], Radial Basis Function (RBF) network with stochastic gradient learning rule [8], and an enhanced resource-allocating neural network for discriminating different patterns of the EEG signals.

The MLP network considered in this study consists of two hidden layers each containing hyperbolic tangent units and a linear output layer. The output layer has three nodes during single-hand movement and five nodes during two-hand movement. The block diagram of a version of RBF network considered in this work is shown in Fig. 3, and the LMS learning algorithm [9] was used for adapting the network parameters.

The architecture of RAM is similar to the RBF networks. The hidden layer is composed of a number of kernel nodes with kernel activation functions [10]. The output of each output neuron is simply a weighted linear summation of the kernel functions:

$$f_j(x) = \alpha_0 + \sum_{i=1}^{M} w_{ij}.k(x) = \sum_{i=1}^{M} w_{ij}.G\left[\frac{\|x - c_i\|}{\sigma_i}\right] \qquad (1)$$

where $x \in R^n$ is the input vector, M is the number of kernel nodes in the hidden layer, w_{ij} $(1 \le i \le M)$ is the vector of weights from the i-th kernel node to the output node j, $\|\bullet\|$ is Euclidean distance, and $\boldsymbol{k}$ is a radial symmetric kernel function. A Gaussian function is chosen as the kernel function. The vectors $\boldsymbol{C_i}$ represent the locations of the kernel functions in $\boldsymbol{R^n}$. Finally, $\boldsymbol{\sigma_i}$ is the smoothing factor or kernel bandwidth of the i-th kernel node. The learning process of RAN involves of allocation of new hidden units as well as adaptation of network parameters. The network begins with no hidden units and grows **by** allocating new hidden units if the following two conditions are satisfied:

$$\|x_n - \mu_{nr}\| > \varepsilon_n$$
$$|e_n| = |y_n - f(x_n)| > e_{\min}$$

where μ_{nr} is the center, which is nearest to x_n, ε_n and $e_{\min}$ are thresholds to be selected appropriately. If the growth criterion is not satisfied, a hidden unit is not added but the network parameters are adapted by using the LMS algorithm.

The networks were trained with data obtained during 70% of the experimental trials and were validated with data obtained during 30% of the subsequent trials. During the training, the feature vector was randomly selected from the training sets and then fed into the network.

To assess the robustness of the proposed scheme in detecting the voluntary hand movement, three different data sets were created for training and evaluating the network during each experiment day.

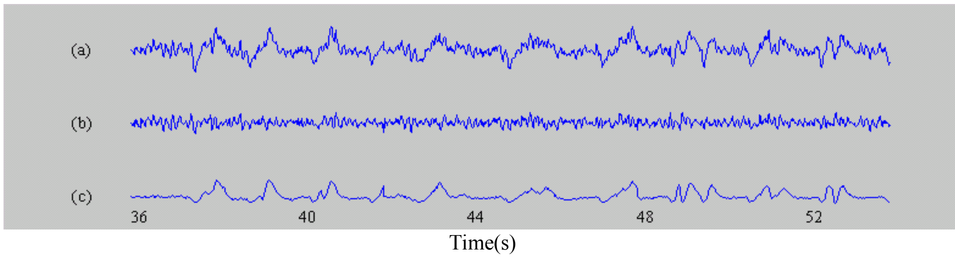

Fig. 2. Eye blink artifact suppression using neural adaptive filter: (a) recorded EEG from position F_3; (b) artifact-free EEG; (c) eye blink data recorded from electrode placed on the forehead above the left brow line.

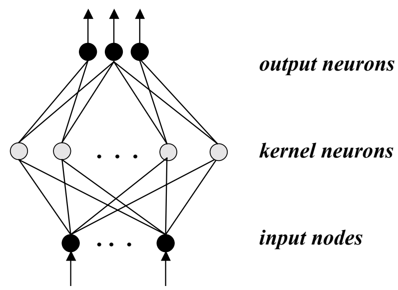

Fig. 3. Architecture of the radial basis function network used for single-hand movement detection.

VI. RESULTS

For each of the three data sets obtained during each experiment day, a neural network was trained and evaluated. Then the results were averaged.

A. Single-Hand Movement

A MLP network with two hidden layers each containing 5 hyperbolic tangent units and three linear output nodes was considered. Table I summarizes the average classification accuracy obtained using MLP networks after 5000 training epochs, for different feature vectors, on different days. It is observed that an average classification accuracy of **98.74%** is achieved over all days using the feature vector (P_α/P_T, P_β/P_T, P_β/P_α). Almost the same results are obtained using the feature vectors (MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α) and (MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α, SV).

Table II shows the results of single-trial EEG classification obtained using RBF network with 15 kernel nodes and three output nodes after 2000 training epochs on different days on the same subject. An average classification accuracy of **97.71%** on novel data is obtained using the feature vectored (MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α, SV).

Table III shows the performance of the enhanced RAN in detecting the single-hand movements after 50 training epochs over the five experiment days. It is observed that an average classification accuracy of **98.82%** is obtained. Note that the performance of the RAN is almost the same over the different experiment days.

B. Two-Hand Movement

Table IV shows the two-hand movement detection results obtained by the back propagation neural network with two hidden layers each containing 10 neurons and five linear output nodes. An average correct classification rate of **96.4%** is obtained over the five days when the vector (P_α/P_T, P_β/P_T, P_β/P_α) is used as the feature vector. Almost the same results can be obtained using the feature vectors (MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α) and (MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α, SV). The results of this analysis show that the feature vector (P_α/P_T, P_β/P_T, P_β/P_α) provides the best classification accuracies during single-hand movement as well as during two-hand movement when the MLP network is used as the classifier.

The results of two-hand movement detection using the RBF network with 25 hidden neurons after 5000 training epochs are summarized in Table V. Once again, the feature vector (MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α, SV) provides the best two-hand classification accuracy when the RBF neural network is used as the classifier. The mean correct classification rate is **95.67%.**

REFERENCES

[1] L. Deecke, "Distribution of readiness potential, pre-motion positivity, and motor potential of the human cerebral cortex preceding voluntary finger movement", *Exp. Brain Res,* vol. 7, pp. 158-168, 1969.

[2] A. Hiraiwa, K. Shimohara, and Y. Tokunaga, "EEG topography recognition by neural networks," *IEEE Eng. Med. Biol.* Sept. 1990.

[3] M. Peltoranta and G. Pfurtscheller, "Neural network based classification of non-averaged event-related EEG responses," *Med. & Biol. Eng. & Comput*., vol. 32 1994

[4] J. Kalcher, D. Flotzinger, Ch. Neuper, S. Golly, and G. Pfurtscheller, "Graz brain-computer interface II: towards communication between humans and computers based on online classification of three different EEG patterns," *Med. & Biol. Eng. & Comput*., vol. 34, 1996.

[5] B. O. Peters, G. Pfurtscheller, and H. Flyvbjerg, "Mining multi-channel EEG for its information content: an ANN-based method for a brain-computer interface," *Neural Networks*, vol. 11, pp. 1429-1433, 1998.

[6] A. Erfanian and S. Moghadas, "Prediction of hand movement from the event-related EEG using neural network," in *Proc. Int. Conf. IEEE/EMBS*, Atlanta GA USA, vol. 21, 1999.

[7] A. Aarabi and A. Erfanian, "Neural adaptive filters for estimating the brainstem auditory evoked potential," in *Proc. Int. Conf. IEEE/EMBS*, Atlanta GA USA, vol. 21, 1999.

[8] S. Hayken, *Adaptive Filter Theory*, Prentice-Hall, Inc, 1996.

[9] S. Hayken, *Neural Networks*, Prentice-Hall, Inc, 1999.

[10] J. Platt, "A resource-allocation network for for function interpulatin," *Neural Computa.,* vol. 3, no. 2, pp. 213-225, 1991.

TABLE I
AVERAGE DETECTION ACCURACIES OF THE SINGLE-HAND MOVEMENTS ON DIFFERENT DAYS, USING A MLP NETWORK WITH TWO HIDDEN LAYERS EACH CONTAINING 5 HYPERBOLIC TANGENT UNITS AND THREE LINEAR OUTPUT NODES AFTER 5000 TRAINING EPOCHS.

Feature Vectors	No. of Input Nodes	*Day 1*	*Day 2*	*Day 3*	*Day 4*	*Day 5*	*Mean*	*Variance*
P_α/P_T, P_β/P_T, P_β/P_α	3×3	97.78	98.52	99.26	99.63	98.52	98.74	0.72
MAV, Var	2×3	98.33	82.96	86.66	77.78	84.82	86.11	7.59
MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α	5×3	97.22	98.89	99.26	93.70	98.89	97.59	2.32
MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α, SV	6×3	96.67	98.15	100.0	97.04	98.15	98.00	1.30
MAV, Var, P_α/P_T, SV	4×3	98.33	95.18	96.30	74.44	95.18	91.89	9.84
MAV, Var, P_β/P_T, SV	4×3	96.67	98.89	96.30	73.71	98.52	92.82	10.75
SV	1×3	93.89	83.33	80.00	44.07	65.19	73.30	19.30

TABLE II
AVERAGE DETECTION ACCURACIES OF THE SINGLE-HAND MOVEMENTS ON DIFFERENT DAYS, USING AN RBF NETWORK WITH 15 HIDDEN NEURONS AND THREE OUTPUT NODES AFTER 2000 TRAINING EPOCHS

Feature Vectors	No. of Input Nodes	*Day 1*	*Day 2*	*Day 3*	*Day 4*	*Day 5*	*Mean*	*Variance*
P_α/P_T, P_β/P_T, P_β/P_α	3×3	80.00	93.33	100.0	98.89	99.26	94.30	8.42
MAV, Var	2×3	97.78	80.00	69.26	53.70	75.93	75.33	16.05
MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α	5×3	97.22	97.78	99.63	92.96	99.26	97.37	2.66
MAV, Var, P_α/P_T, P_β/P_T,P_β/P_α, SV	6×3	96.67	97.41	98.15	96.67	99.63	97.71	1.24
MAV, Var, P_α/P_T, SV	4×3	97.22	93.70	93.33	71.85	80.74	87.37	10.69
MAV, Var, P_β/P_T, SV	4×3	96.66	94.82	92.96	71.85	78.15	86.89	11.16
SV	1×3	92.78	84.44	77.41	45.93	59.63	72.04	19.03

TABLE III
AVERAGE CLASSIFICATION ACCURACIES OF THE EEG PATTERNS DURING SINGLE HAND MOVEMENTS ON DIFFERENT DAYS, USING RESOURCE ALLOCATING NETWORK AFTER 50 TRAINING EPOCHS

Feature Vectors	No. of Input Nodes	*Day 1*	*Day 2*	*Day 3*	*Day 4*	*Day 5*	*Mean*	*Variance*
set1	3×6	98.33	100.0	100.0	97.78	100.0	99.22	1.1
set 2	3×6	96.67	100.0	100.0	100.0	99.00	99.13	1.4
set 3	3×6	95.00	98.89	97.78	98.89	98.89	97.89	1.69
Mean		96.67	99.63	99.26	98.89	99.30	98.75	1.19

TABLE IV
AVERAGE DETECTION ACCURACIES OF THE TWO-HAND MOVEMENTS ON DIFFERENT DAYS, USING A MLP NETWORK WITH TWO HIDDEN LAYERS EACH CONTAINING 10 HYPERBOLIC TANGENT UNITS AND FIVE LINEAR OUTPUT NODES AFTER 5000 TRAINING EPOCHS

Feature Vectors	No. of Input Nodes	*Day 1*	*Day 2*	*Day 3*	*Day 4*	*Day 5*	*Mean*	*Variance*
P_α/P_T, P_β/P_T, P_β/P_α	3×3	98.00	96.00	98.33	97.67	92.00	96.40	2.62
MAV, Var	2×3	77.67	69.67	69.67	50.33	56.33	64.73	11.12
MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α	5×3	96.00	93.67	97.00	93.00	92.33	94.40	2.01
MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α, SV	6×3	94.67	93.67	98.33	96.67	91.67	95.00	2.59
MAV, Var, P_α/P_T, SV	4×3	84.33	84.00	80.33	83.00	69.33	80.20	6.28
MAV, Var, P_β/P_T, SV	4×3	89.67	85.67	84.67	95.00	68.00	84.60	10.13
SV	1×3	66.00	53.67	41.00	40.67	33.33	46.93	12.93

TABLE V
AVERAGE DETECTION ACCURACIES OF THE TWO-HAND MOVEMENTS ON DIFFERENT DAYS, USING AN RBF NETWORK WITH 25 HIDDEN NEURONS AND FIVE OUTPUT NODES AFTER 5000 TRAINING EPOCHS

Feature Vectors	No. of Input Nodes	*Day 1*	*Day 2*	*Day 3*	*Day 4*	*Day 5*	*Mean*	*Variance*
P_α/P_T, P_β/P_T, P_β/P_α	3×3	86.33	71.67	87.67	91.67	75.67	82.60	8.51
MAV, Var	2×3	64.33	47.33	34.00	22.67	31.00	39.87	16.30
MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α	5×3	93.67	88.00	96.33	95.00	90.67	92.73	3.38
MAV, Var, P_α/P_T, P_β/P_T, P_β/P_α, SV	6×3	95.00	96.67	97.33	94.67	94.67	95.67	1.25
MAV, Var, P_α/P_T, SV	4×3	85.67	83.33	77.33	59.00	52.67	71.60	14.88
MAV, Var, P_β/P_T, SV	4×3	87.00	83.67	82.00	72.33	59.67	76.93	11.09
SV	1×3	49.67	46.00	25.67	20.00	33.00	34.87	12.77